A Novel Semi-Fragile Watermarking Scheme with Iterative Restoration

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Abstract. In this paper, a novel semi-fragile watermarking scheme utilizing Iterative Restoration techniques is proposed. The scheme embeds a restricted set of restoration data in the transform domain of a cover image, which equates to a highly compressed copy of that image. If tampering occurs, the image is authenticated by comparing the extracted watermark data to encrypted data from a key file to detect changes. The restricted restoration data extracted from the image is then passed through traditional image restoration techniques such as Lucy-Richardson Iterative restoration and Blind Deconvolution, in an attempt to improve the restoration data before inserting back into tampered regions, to give an initial reconstruction of the manipulated locations. The technique can maintain a high watermarked image and restored region image quality of above 34 dB PSNR, as well as survive up to 30% JPEG Compression and other non-geometric attacks such as Gaussian noise, copy and paste, and region removal. The Average Detection Rate (ADR) is high, and Lucy-Richardson Iteration demonstrates up to a 25% improvement of subjective restoration quality compared to previous techniques such as LSB restoration schemes which use direct restoration techniques.

Keywords: Watermarking, Authentication, Image Restoration, DCT, Lucy-Richardson, Blind Deconvolution, Wiener Filtering, Regularised Filtering.

1 Introduction

Semi-Fragile authentication Watermarking is a process that can be utilised to allow an image to be authenticated when tampering occurs. The requirement of this watermarking technique is that it should be able to tolerate reasonable levels of non-malicious manipulation, meanwhile still authenticating tampered regions of the image and restoring them.

Previous work in this area has been related to authentication of tampered regions. This scheme introduces a self-restoration technique that is capable of restoring tampered regions once localisation of tampered regions has taken place. Existing work in the watermark authentication and restoration field, such as Fridrich's LSB Restoration scheme [1], and Barni's DCT watermarking [2] have highlighted some key trade-offs between the subjective quality of the watermarked image and the robustness and quality of the restoration data. In Fridrich's work, the authentication and restoration watermark data is constructed by extracting key coefficients from each

8x8 sub-block in the DCT transform domain of an image. These coefficients are then quantised and converted to binary – equating to a highly compressed copy of the image. The binary watermark is then shuffled and inserted directly into the LSB plane of the image. If tampering occurs, the image can be authenticated by comparing the extracted watermark to the original, and then damaged regions can be restored by inverse quantising and reconstructing the restoration data for that location. The watermarked and restored image quality is high, but the scheme embeds the restoration data in the LSB plane, causing the watermark data to be extremely fragile.

In Barni's DCT method, the authentication and restoration data is embedded in the transform domain by manipulating coefficient values, creating a much more robust scheme, however, the watermarked image quality and restoration quality are reduced.

Another form of image manipulation is in the form of traditional restoration schemes such as filtering and iterative algorithms. These techniques have been used for many years to aid in restoring images that have been damaged by noise, blurring and other forms of degradation. Each of these schemes aims to act as an inverse to the original degradation function that created the damaged image.

The scheme proposed in this paper attempts to combine the positives of both the LSB and DCT watermarking techniques, by embedding a restricted set of restoration data in the transform domain, consisting of quantized coefficient values. The transform domain is used to ensure that the technique can survive reasonable levels of JPEG compression and other non-geometric attacks. The requirement for the watermark data is to be small in size, so that the cover image suffers the smallest amount of degradation. Due to the small size of the restoration data, the quality of restored regions can suffer. To combat this issue, the use of traditional image restoration techniques such as iterative restoration are suggested. By applying these techniques on the restricted watermark data, the quality of the restoration data can be improved before being used.

The objective of this research is to investigate the suitability of using a restricted set of restoration data embedded in the transform domain for self-restoration watermarking, and the optimum traditional image restoration scheme for restoring the restricted data.

2 Traditional Image Restoration Techniques

Four traditional image restoration techniques were selected, based on research carried out into existing restoration schemes. Two different types of technique – filter and iterative, were selected.

2.1 Wiener Filter

The first selected was the Wiener Filter. The idea of using a Wiener filter came from Hillery and Chin's work [4]. Their paper investigates using linear Wiener filters, as well as iterative Wiener filtering to reduce the Mean Square Error when restoring images. The model for the Wiener filter can be described as follows.

Consider the standard equation to model a signal with noise:

$$y[n]=x[n]+n[n] \quad \textbf{(1)}$$

The original signal x can be approximated (x□), by passing y[n] through a filter ‘h’. The aim of the filter is to minimise the difference between x and x□. This can be achieved by first minimising the Mean Square Error between the two. Since we know that x□ is h convolved with y, we have:

$$\| x – x*y \|_{2} \quad \textbf{(2)}$$

We can expand this expression known algebraic rules. Then we can take the Fourier transform of the expression to find the power spectra.

$$\sum_{j}((X_j\text{-}H_jY_j)^2) \quad \textbf{(3)}$$

$$\sum_{j}((X_j\text{-}H_j(X_j + N_j))^2) \quad \textbf{(4)}$$

We minimize this expression over H and in the end after all the simplification we get the following formula for H, our filter optimized to minimize the difference between x and x□ .

$$H(f)= \frac{(|Xf|)^2}{(|Xf|)^2 + (|Nf|)^2} \quad \textbf{(5)}$$

Where X(f) is the power of the signal and N(f) is the power of the noise.

2.2 Regularised Filter

This restoration technique is described in a paper by Mesarovicet al [5]. The technique attempts to solve the issue of inversing the degradation process by formulating the restored image solution as a set of linear equations which the Regularised filter is used to solve [5].

2.3 Lucy-Richardson Iterative Restoration

Fish, Brinicombe, Pike, and Walker experimented with using the Lucy-Richardson Iterative restoration technique in their paper [6]. The research suggests that Lucy-Richardson Iteration has a more superior performance compared to other blind restoration techniques [6]. The model for Lucy-Richardson Iteration can be described as follows:

$$c_i = \sum_j p_{ij} u_j \tag{1}$$

$$\mathbf{u}_j^{(t+1)} = \mathbf{u}_j^{(t)} \sum_i \frac{c_i}{\mathbf{c}_i} p_{ij} \tag{6}$$

where

$$\mathbf{c}_i = \sum_j \mathbf{u}_j^{(t)} p_{ij}$$

If this iteration converges, it converges to the maximum likelihood solution for u_j.

2.4 Blind Deconvolution

In the paper by Kundur and Hatzinakos, the use of Blind Deconvolution to restore images that had been degraded linearly is proposed [7]. The scheme attempted to restore images without any prior knowledge of the original image. The technique can be described as follows:

3 Method

The semi-fragile watermarking scheme with iterative restoration involved two main steps. Each is described in detail in the following headings.

3.1 Watermark Embedding

The first stage of the watermarking technique is to embed a set of restricted restoration data into the transform domain of the image. Figure 2 displays the embedding process for the restoration scheme.

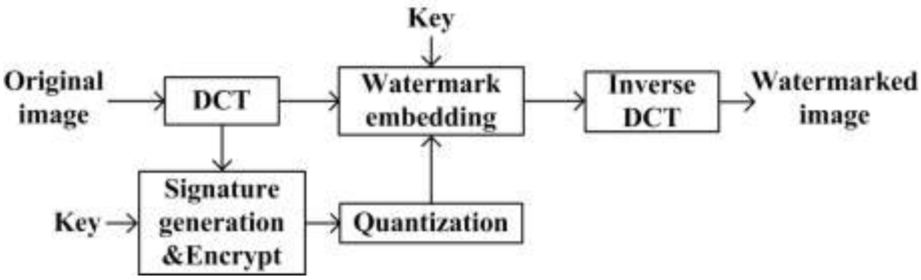

Fig. 1. Watermark creation and embedding process.

The embedding technique starts by constructing the restoration data which is to be embedded as a watermark in the image. To do this, a greyscale image is 8x8 sub-blocked and passed through the DCT transform. Next, signature generation occurs. The first *n* coefficients are extracted from each 8x8 sub-block, and the values are then quantised using a predefined quantisation matrix. The values are then encrypted using a pre-shared key to increase the security of the watermarked data. This compresses the values so they take up a minimum amount of space during watermarking. At this point, the restoration data that is to be embedded as a watermark has been created, and consists of a highly compressed copy of the image to protect, as shown in Figure 2.

Fig. 2. Example of restricted restoration data to be embedded as watermark.

The watermark information is next shuffled to ensure that any region of the image that has been tampered with will not contain the restoration data for that region, therefore losing the restoration data through manipulation.

At this stage, the watermarked data is ready to be inserted into the transform domain of the cover image. To do this, the coefficient values of the cover image are manipulated to contain the watermark information. Embedding the watermark information consists of writing watermark data over existing coefficient values, so that during the extraction phase, the change in coefficient value can be used to determine if the bit embedded was a ‘1’ or a ‘0’. The process is described as follows.

$$x' = \begin{cases} x, & (x \geq \tau \wedge w = 1) \vee (w \leq -\tau \wedge w = 0) \\ \alpha, & (x < \tau \wedge w = 1) \\ -\alpha, & (x > \tau \wedge w = 0) \end{cases}$$

$$x' \qquad x \qquad w$$

Where $\tau > 0$ is the threshold which controls the perceptual quality of the watermarked image and α is a constant between $\frac{\tau}{2}$ to τ

x’ is the watermarked coefficient
x is the original coefficient and
w is the watermark data

Figure 2 displays the entire embedding process, from generating the restricted restoration data, to embedding the watermark information.

Some parameters were made available during the embedding procedure to give a varied set of results.

The coefficient mask determines the location of the coefficients to be manipulated to contain the watermark information. This can consist of areas of high, middle or low frequency.

The quantisation level could be specified, with the option of ‘low’, ‘medium’ or ‘high’. The extracted coefficient values that were to be used as restoration data were then compressed with the specified level. The reason for supporting different levels of quantisation was to see how the watermarked image and restoration data were affected. By applying large levels of quantisation, the size of the watermarked information was reduced, possibly improving the quality of the watermarked image.

The coefficient location values available were ‘low’, ‘medium’ and ‘high’. The reason for supporting these values was to investigate the affect that the coefficient location had on the watermark image quality and the quality of the restored image.

An adaptive embedding technique has been designed that adapts the number of coefficients used depending on the image type. The method works by embedding the maximum amount of coefficients available in the image, and then measuring the PSNR of the watermarked image. If the quality is above a fixed threshold (~30dB), the watermarked image is passed. However, if the watermarked image quality is poor, then the number of coefficients used is decremented, and the embedding scheme is executed again. This process is repeated until an acceptable watermarked image quality is achieved, and also ensures that the best quality restoration data is used.

3.1 Watermark Authentication and Restoration

Once the watermark was embedded, the process of extracting the embedded bits was required.

To extract the embedded watermark, the process of sub-blocking and performing a DCT was carried out. The watermark values were extracted from the coefficients located at the mask embedded in. The pre-shared key is used to decrypt and re-shuffle the watermarked information. With the retrieved values, each was checked to see if the value was greater or less than the constant y defined in the key file. If it was greater, a '1' was stored as the value embedded in that coefficient $w^{'}$, otherwise a value of '0' was stored.

$$w^{'} = \begin{cases} 1, & y \geq \alpha \\ 0, & y < \alpha \end{cases}$$

With all the retrieved bits, the binary watermark that was originally embedded could be reconstructed into its original form. To do this, the extracted data was inverse quantised and shuffled back into its original. This was required for the next step and main goal of this system, authentication and restoration of tampered regions of an image.

Using the extracted watermark information, the process of authentication could take place. Authentication works by comparing the extracted watermark information to the original predefined information, to check for inconsistencies. In this design, the authentication data acts also as the restoration data. If the system was to be used for commercial purposes, then authentication bits could also be embedded alongside the restoration data.

$$diff = \frac{num(a \cap b)}{num(a)}$$

where a is the current n bits of the predefined watermark
b is the current n bits of the extracted watermark

This formula works out the difference between bits in the predefined and extracted watermark information by evaluating what percentage of the predefined watermark match the corresponding bit for the extracted. If the difference measured is below a threshold T, then the region of the cover image at the location where that watermark information was extracted from is marked as tampered by filling with red pixels.

Once the extracted watermark had been compared to the original to find manipulated regions, the image was successfully authenticated. The next requirement was to restore the tampered regions. Figure 3 displays the key steps for watermark extraction and restoration.

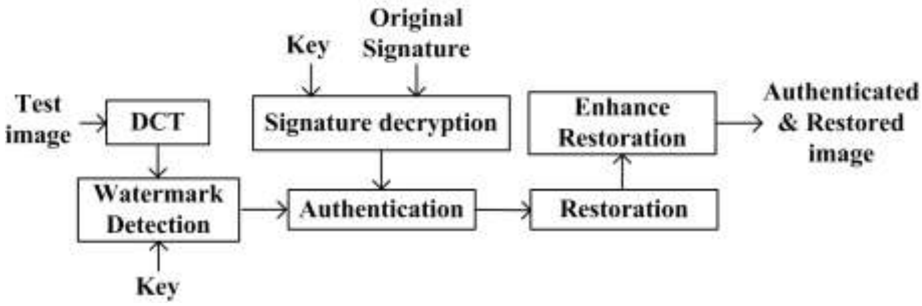

Fig. 3. Watermark extraction and restoration of tampered regions.

The restoration process consisted of attempting to improve the initial quality of the extracted restoration data, using different image restoration techniques.

First, the directly extracted restoration data without any advanced restoration techniques was inserted into the authenticated regions of the image. This image was used as a comparison image against the output from each of the other restoration techniques such as Lucy-Richardson Iterative restoration, to measure which restoration method gave the best restored image regions.

Next, the extracted watermark restoration data was passed to each of the restoration techniques – Lucy-Richardson iterative restoration, Blind Deconvolution, Wiener filtering and Regularised filtering. Each performed their restoration on the data, before inserting the advanced restored data into the tampered regions of the image. Once each had completed their attempt at the restoration, the outputs were displayed side-by-side to be compared by the user. The results from testing this process on different images, with varying forms of manipulation, was carried out to determine which of the advanced restoration techniques performed best.

During the advanced restoration stage, the iterative techniques had a slightly different method of deciding how to best restore the image. Due to the fact that the iterative techniques – Lucy-Richardson and Blind Deconvolution, both allowed for the selection of how many iterations to perform on the extracted image, an optimum number need to be chosen. If each technique performed too many or too little iterations, the image quality could deteriorate.

To solve this issue, an Optimum Iteration Analysis (OIA) method was designed. This simple method consisted of the following steps:

- Take extracted watermark image
- Perform iterations between 1 and 10
- For each iteration, measure and store the PSNR of the current image with the original
- After 10 iterations, find the highest PSNR results and store as the optimum iteration number
- Perform iterative technique using the optimum iteration number
- Insert restored improved image back into tampered authenticated regions

4 Results

To evaluate the effectiveness of the semi-fragile restoration technique proposed in this paper, experiments into the watermarked image quality, restored image quality and robustness of the restoration data were carried out. Three different test images were used to evaluate the scheme and its effectiveness with different styles of image – a photograph, painting and computer generated image.

Fig. 4. The three images used during testing.

4.1 Watermarked Image Quality

The first set of results measured the quality of the watermarked image against the original image prior to embedding. It is important that this watermarking scheme does not degrade the visual quality of the cover image during embedding. Images with a PSNR above 30 dB represent an acceptable level of quality.

The number of coefficients used as restoration data was varied between 1-5, and was embedded in each of the test images. The results showed that as the number of coefficients increased, the visual quality of the watermarked image decreased. For example, by embedding 1 coefficient in the Lena image, the PSNR was over 41 dB, however, when increasing the coefficient number to 5 the watermarked image quality was reduced to 34 dB. This highlighted a trade-off between the watermarked image quality and restoration quality, as the watermark quality was higher when the coefficient number was lower, but the restoration quality suffered because of this.

Due to the trade-off between the watermarked image quality and restoration quality, the use of 2 coefficients proved to meet the requirement for watermarked image quality versus restoration quality.

4.2 Restored Subjective Quality

Work by Nemethova et al has shown that the Peak Signal-to-Noise Ration (PSNR) does not reflect well the quality of images suffering from JPEG compression and other similar artefacts [8]. To overcome this issue, some metrics that had been designed to take advantage of known characteristics of the Human Visual System

(HVS) were experimented with, with the hope that a better correlation to subjective quality would be found, and therefore identify which restoration technique proved most successfully in improving the restricted restoration data [9]. A description of each of the metrics experimented with is provided below.

The Visual Information Fidelity (VIF) algorithm was first described by Sheikh and Bovik [10]. The technique proposed to measure the Shannon information shared between two images – the original and the tampered images. Once the Shannon information has been quantified, this can be used as an information fidelity metric [10].

The PSNR-HVS-M metric is a technique developed by Ponomarenko et al [11]. The PSNR-HVS-M method is a Peak Signal-to-Noise Ratio metric taking into account the Contrast Sensitivity Function (CSF) and between-coefficient contrast masking of DCT basis functions [11]. The process involves passing the original image and the tampered image through the DCT transform so the frequency domain is visible. The difference between each set of frequencies is then calculated. A contrast mask is then applied, which reduces the overall contrast level in the difference image. Finally, the Mean Square Error (MSE) of the output image is calculated to give a measurable value of the difference between the images.

The Structural Similarity Index (MSSIM) was a technique devised by Wang et al[9]. The method is based on the degradation of structural information in an image, and attempts to measure the attributes that reflect the key structure and objects of importance in an image [12]. The technique splits the contrast, luminance and structure of the images to compare them separately [12].

To setup this experiment, a fixed region of one of the images was damaged by a region removal attack (the nose region of the Lena image). The region was then restored using each of the different restoration algorithms – Direct restoration, Lucy-Richardson, Blind Deconvolution, Wiener Filter and Regularised Filter. Each was given a number, and the image displayed in Figure 7 was uploaded to the Internet. Users from different forums, some image processing and others general forums with no links to digital image processing, were asked to rate the images in order of visual quality. The results were tallied and the 50 responses are shown in Figure 8.

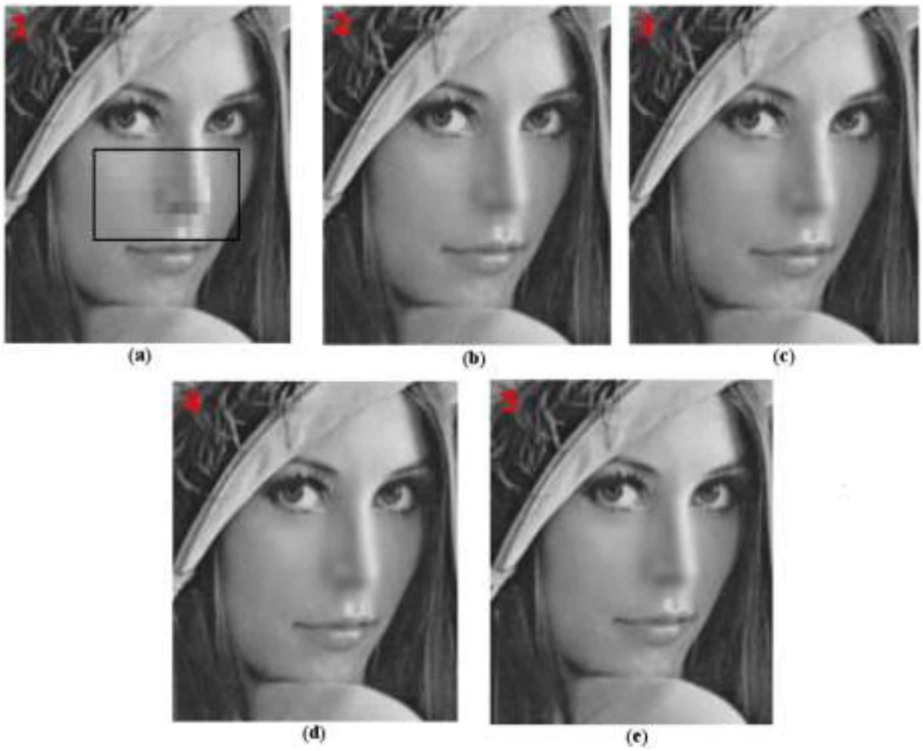

Fig. 5. The results of the different restoration algorithms. From left to right, top to bottom – Direct restoration, Lucy-Richardson, Blind Deconvolution, Wiener Filter and Regularised Filter.

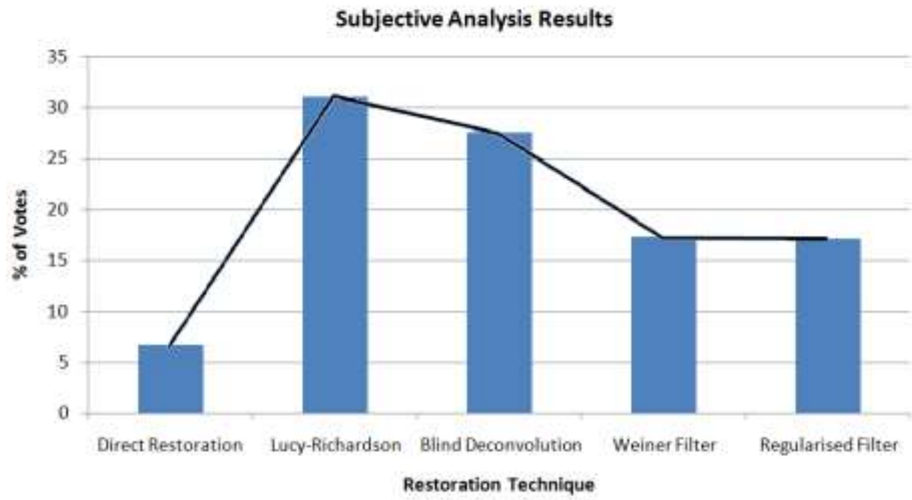

Fig. 6. Subjective analysis results from 50 people.

It is clear from these results that people believed that Lucy-Richardson Iterative restoration gave the best subjective quality results. This trend was compared to the results of measuring each image against each of the four metrics. PSNR-HVSM showed that it followed the subjective trend more closely than any of the other techniques (as shown in Figure 9).

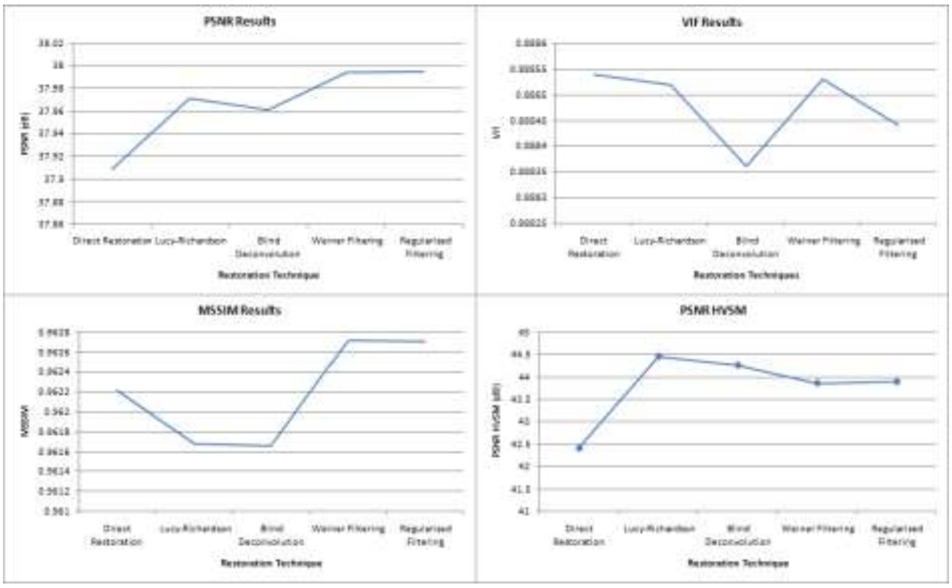

Fig. 7. PSNR-HVSM results from measuring the restored regions of different techniques.

These results showed us that the restoration technique that most improved the restricted restoration data was Lucy-Richardson Iterative restoration, and the metric that most closely measured the subjective quality was PSNR-HVSM.

4.3 Watermarked Image Robustness

The final set of tests measured the robustness of the restoration data embedded as a watermark. Different non-geometric attacks were used to degrade the image, such as JPEG Compression, Salt and Pepper noise, region removal, copy and paste and Gaussian noise.

The first test shows the robustness of the watermarked restoration data against increasing levels of JPEG compression. The watermark location was varied between high, medium and low frequency block locations.

The results shown in Figure 10 show that the restoration data can survive up to a QF of 70 when embedding in low frequency locations. This is due to the fact that JPEG compression removes details from high frequency regions before low, manipulating any restoration data that may be embedded in higher frequency locations sooner.

The graph shown in Figure 11 displays the results of testing different watermark locations against increasing levels of Gaussian noise. The results show that by embedding in areas of high or medium frequencies, the restoration data is of a better quality against attacks such as Gaussian noise compared to areas of low frequency.

4.4 Watermarked Image Robustness

To investigate the possible improvements that the advanced restoration schemes – Lucy-Richardson Iteration, Blind Deconvolution, Wiener Filtering and Regularised Filtering could have on the poor quality direct restoration technique, each was experimented with and the results shown below.

The following tables display the results for testing the robustness of the watermark, and the quality of restoration algorithms. For each experiment, the watermarked image was passed through non-malicious manipulation, and then the entire watermark restoration data was extracted. Each of the different restoration techniques was then applied to the restoration data, and the final quality of each recorded.

Table 9 shows the quality of the restored regions after no manipulation has taken place. The results show that each of the advanced restoration techniques outperforms direct restoration by up to 2 dB. Lucy-Richardson Iterative restoration consistently outperforms the other restoration techniques, closely followed by Blind Deconvolution. Both of the filtering techniques – Wiener and Regularised, perform similarly, and Direct Restoration performs the worst. The iterative restoration techniques both outperform the other two filtering schemes. Another observation that can be made from the results is that natural images, such as Lena, perform better than the other two image types.

Table 8: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after no attack.

	Lena	Office	Van Gogh
Direct Restoration	19.01	11.27	14.20
Lucy-Richardson	20.92	11.74	15.44
Blind Deconvolution	20.24	11.73	15.44
Wiener Filter	19.03	11.35	14.24
Regularised Filter	19.02	11.35	14.23

Table 10-14 displays the results for the quality of the restored regions after undergoing different forms of non-malicious manipulation. Again, each of the restoration techniques outperforms Direct Restoration, with the Iterative schemes improving the restored regions by up to 3 dB, compared to the Direct Restoration method.

The results of testing show that for different forms of manipulation to the watermarked image, the Direct Restoration method always performs the worst. Certain manipulation schemes such as JPEG compression, Sharpening and Histogram Equalisation affected the quality of the restored image greater than other techniques such as Gaussian Filtering and Contrast Stretching. For each of the attacks, and for each of the test images, Lucy-Richardson outperformed the other restoration techniques. This was followed closely by Blind Deconvolution. The two filtering techniques also performed similarly. Direct Restoration was always the worst quality restored region.

These tests also highlighted the robustness of the watermarking scheme. The results from Table 9 show that with no manipulation, the PSNR-HVSM value of the restricted restoration data is reasonable for natural images, around 20 dB. After the watermarked image has undergone different non-malicious manipulations, the quality of the restoration data deteriorates at different rates depending on the type of manipulation, dropping to as low as 13 dB after Histogram Equalisation. The watermark proved to be more robust against Gaussian Filtering and Contrast stretching, maintaining a restored region of around 19 dB.

This restoration scheme proved to be more robust against forms of non-malicious manipulation compared to the LSB Restoration scheme described by Fridrich. The Iterative schemes, particularly Lucy-Richardson, showed an improvement over Direct Restoration.

Table 9: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after undergoing 70% JPEG QF.

	Lena	Office	Van Gogh
Direct Restoration	13.15	8.28	10.74
Lucy-Richardson	14.00	9.16	11.64
Blind Deconvolution	14.00	9.16	11.63
Wiener Filter	13.70	8.98	11.15
Regularised Filter	13.70	8.98	11.15

Table 10: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after undergoing Gaussian Filtering.

	Lena	Office	Van Gogh
Direct Restoration	15.68	8.48	7.95
Lucy-Richardson	16.48	9.30	9.10
Blind Deconvolution	16.47	9.30	9.10
Wiener Filter	15.76	9.11	8.81
Regularised Filter	15.77	9.11	8.81

Table 11: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after undergoing Contrast Stretching.

	Lena	Office	Van Gogh
Direct Restoration	17.89	13.34	13.34
Lucy-Richardson	19.22	14.41	14.42
Blind Deconvolution	19.22	14.42	14.41
Wiener Filter	18.15	13.34	13.34
Regularised Filter	17.89	13.46	13.46

Table 12: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after undergoing Sharpening Filter.

	Lena	Office	Van Gogh
Direct Restoration	13.91	6.02	6.20
Lucy-Richardson	16.39	7.91	8.90
Blind Deconvolution	16.39	7.91	8.90
Wiener Filter	15.57	7.62	8.32
Regularised Filter	15.57	7.62	8.32

Table 13: PSNR-HVSM (dB) results for varying restoration schemes, when restoring the entire image after undergoing Histogram Equalisation.

	Lena	Office	Van Gogh
Direct Restoration	13.38	7.60	6.82
Lucy-Richardson	15.69	8.87	8.71
Blind Deconvolution	15.69	8.87	8.71
Wiener Filter	15.15	8.67	8.31
Regularised Filter	15.15	8.679	8.31

5 Summary

Experimentation showed that the DCT scheme with advanced restoration proved to successfully embed and extract a limited set of watermark restoration data, which combined with image restoration techniques such as iterative restoration, could be further improved before use.

With regards to the watermarked image quality, the results from testing suggested that this technique was more suitable for natural images which have an even mix of high and low frequency regions, such as the photograph of Lena. This was shown through measuring the PSNR of the watermarked image when embedding different coefficient numbers. Lena could successfully contain between 1-5 coefficients as restoration data, while maintaining a higher PSNR.

Overall, the semi-fragile watermarking scheme with iterative restoration proved to be extremely successful as a watermark authentication and restoration scheme. The initial design attempting to restrict the amount of information embedded as a watermark in an effort to preserve the quality of the image proved effective. The idea of restoring a restricted data set and applying traditional image restoration techniques showed that the restoration data could be improved before being inserted back into damaged regions of the image. A restriction of this technique was that the scheme appeared to work best for low frequency regions, and not so well for high frequency regions. However, in saying this, even high frequency regions were improved slightly, just not to the extent that low frequency regions were. This left a gap in the technique for possible future work, concentrating on different techniques depending on the properties of the damaged region. This technique proved to be semi-fragile, surviving reasonable amounts of compression, Gaussian noise, copy and paste and region removal attacks. This would make it suitable for a lot of applications in the real world, as it is not as fragile as the LSB Restoration scheme for example. A drawback of this technique is that although the embedding times were quick, the watermark extraction and restoration process was slow. As previously mentioned, these issues could probably be greatly reduced by spending time optimising the code. Overall, the results from this novel DCT Restoration scheme proved very promising. There are some more areas of research yet to cover for this technique that are out of the scope of this current project, but the results shown so far prove that this technique is a viable semi-fragile restoration algorithm.

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